

Separation for the Max-Cut Problem using Target Cuts and Graph Contraction

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Joint work with:

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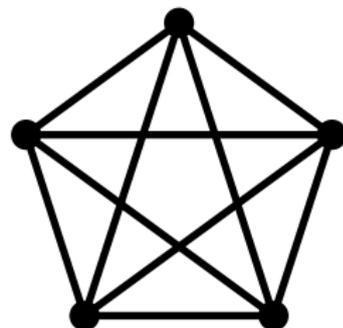
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Klagenfurt, June 4, 2010

- 1 Max-Cut Problem
- 2 Separation using Graph Contraction
- 3 Target Cuts
- 4 Computational Results

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Definition

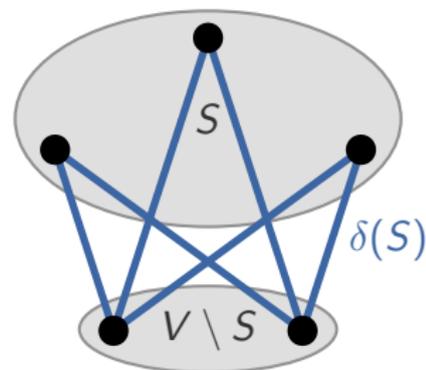
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Any $S \subseteq V$ induces a set $\delta(S)$ of edges with exactly one end in S . The set $\delta(S)$ is called a **cut** of G with **shores** S and $V \setminus S$.

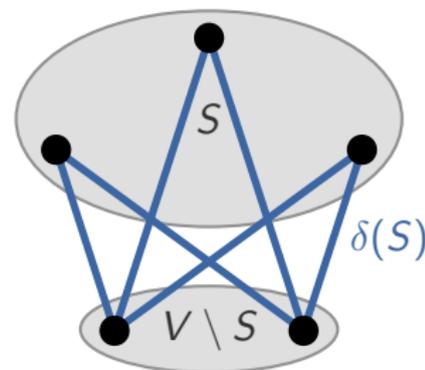


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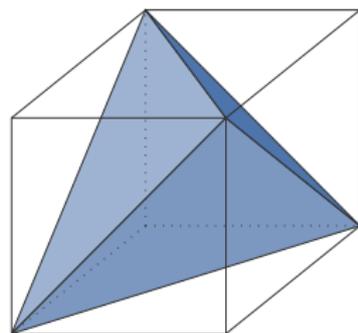
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Finding a cut with maximum aggregate edge weight is known as **max-cut problem**.



Cut polytope $\text{CUT}(G)$

Convex hull of all incidence vectors of cuts of G .



$\text{CUT}(K_3)$

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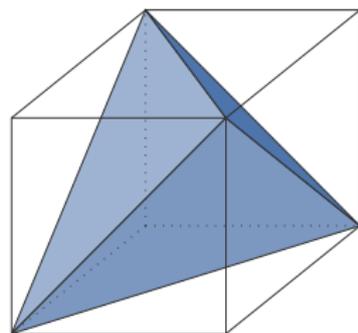
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Semimetric polytope $\text{MET}(G)$

Relaxation of the max-cut IP formulation described by two inequality classes:

Odd-cycle: $x(F) - x(C \setminus F) \leq |F| - 1$, for each cycle C of G ,
for all $F \subseteq C$, $|F|$ odd.

Trivial: $0 \leq x_e \leq 1$, for all $e \in E$.

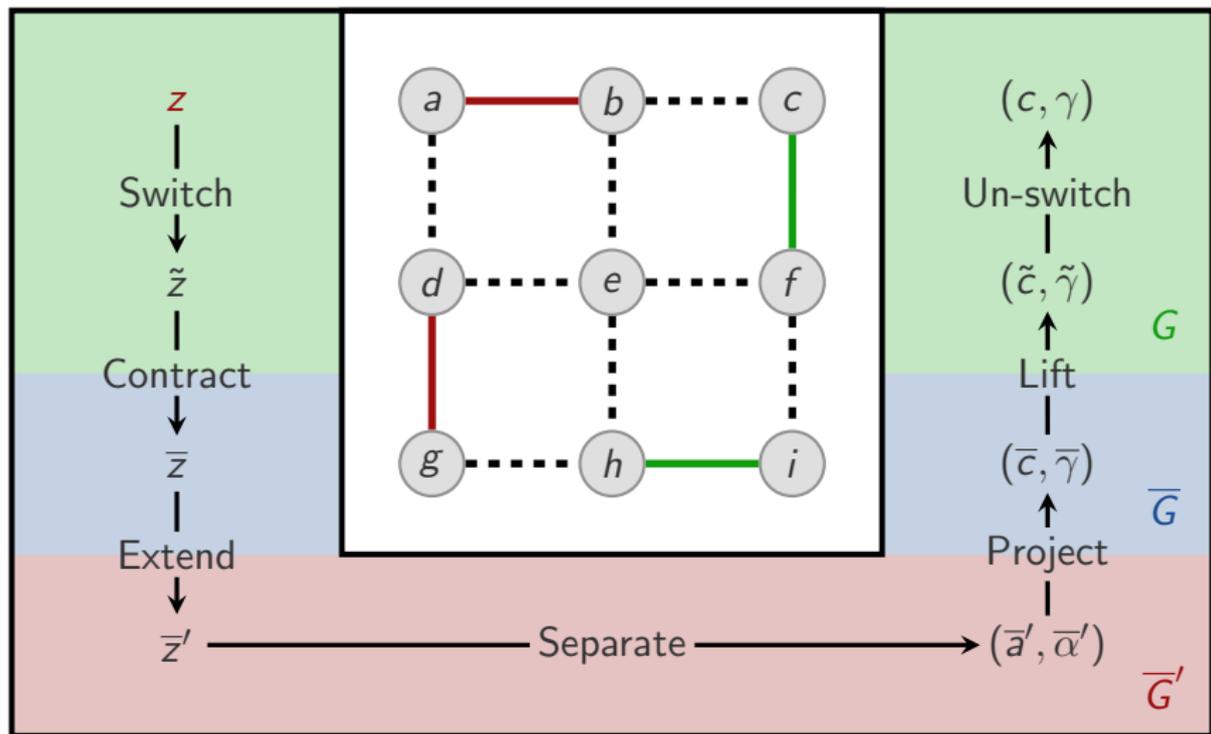


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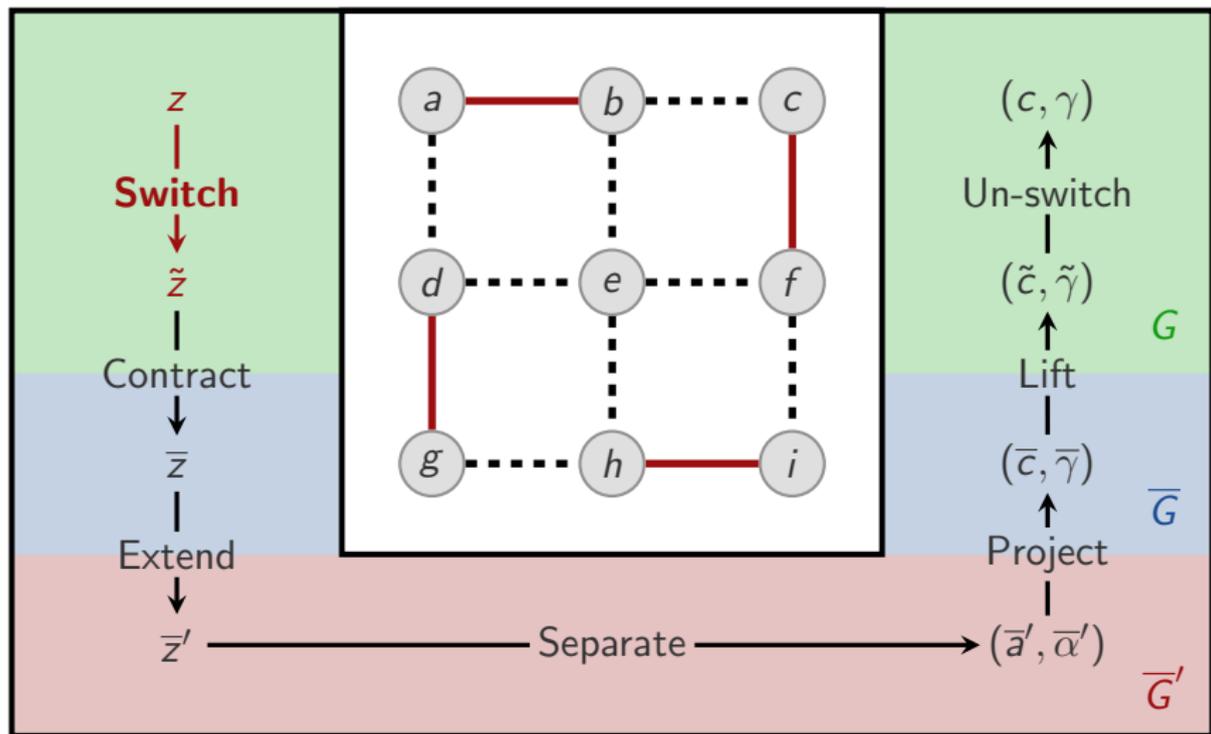
Outline of the Separation using Graph Contraction

Input: LP solution $z \in \text{MET}(G) \setminus \text{CUT}(G)$.



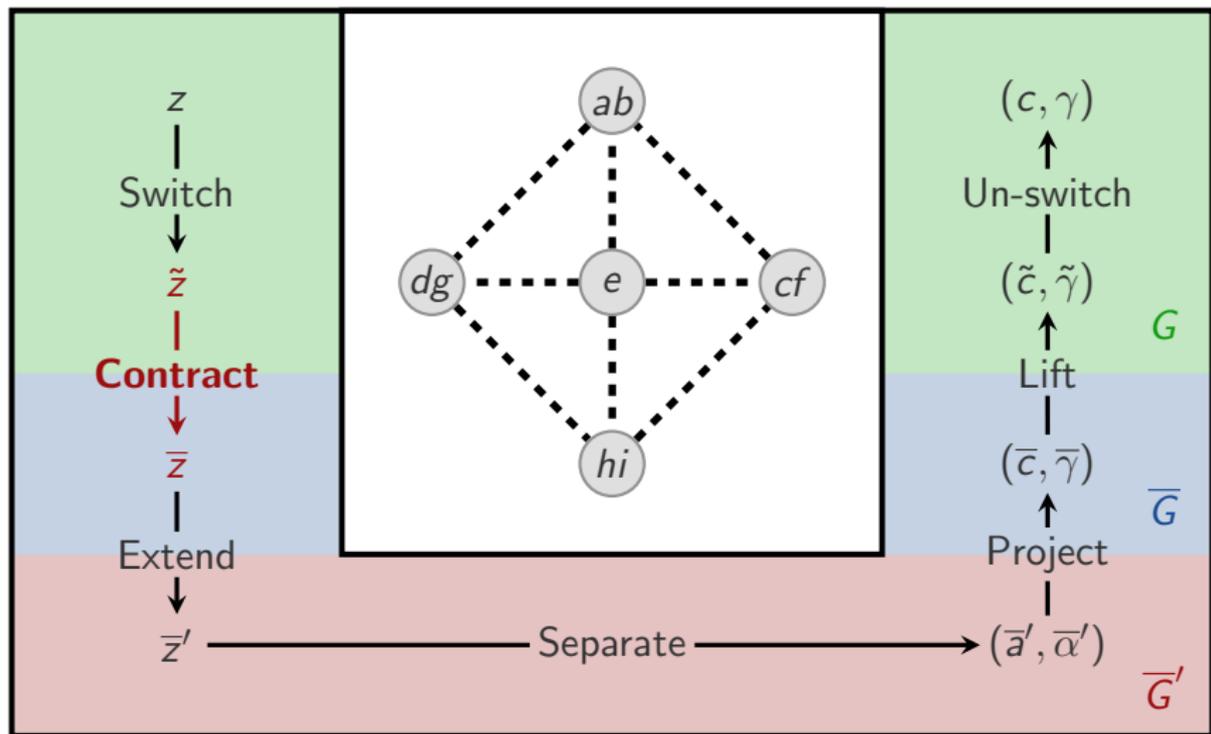
Outline of the Separation using Graph Contraction

Transform 1-edges into 0-edges.



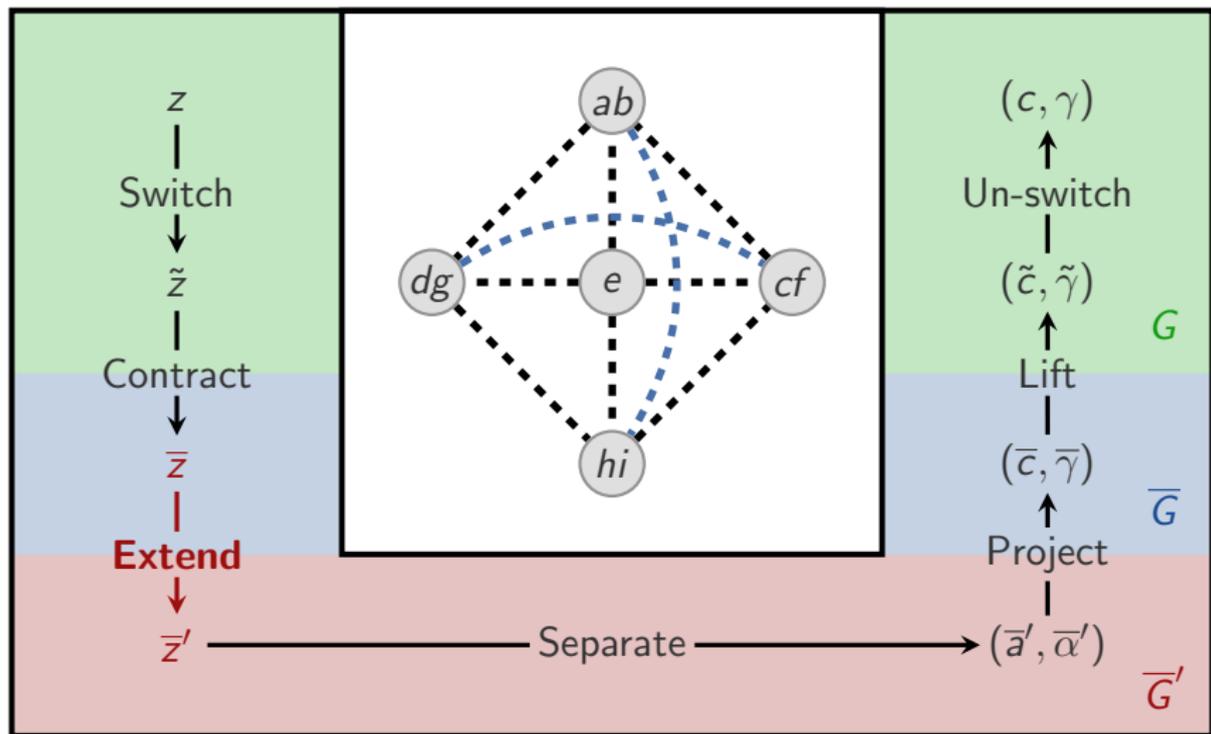
Outline of the Separation using Graph Contraction

Contract **0-edges**. Allows heuristic odd-cycle separation.



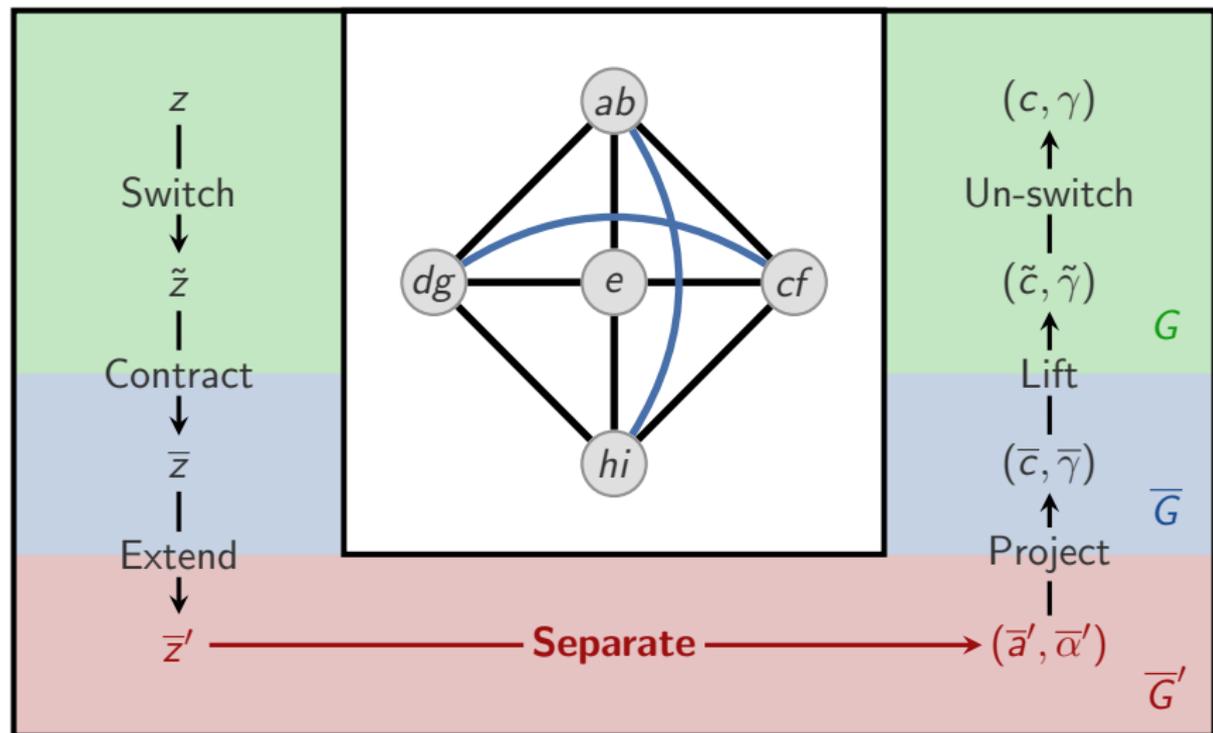
Outline of the Separation using Graph Contraction

Introduce artificial LP values for non-edges.



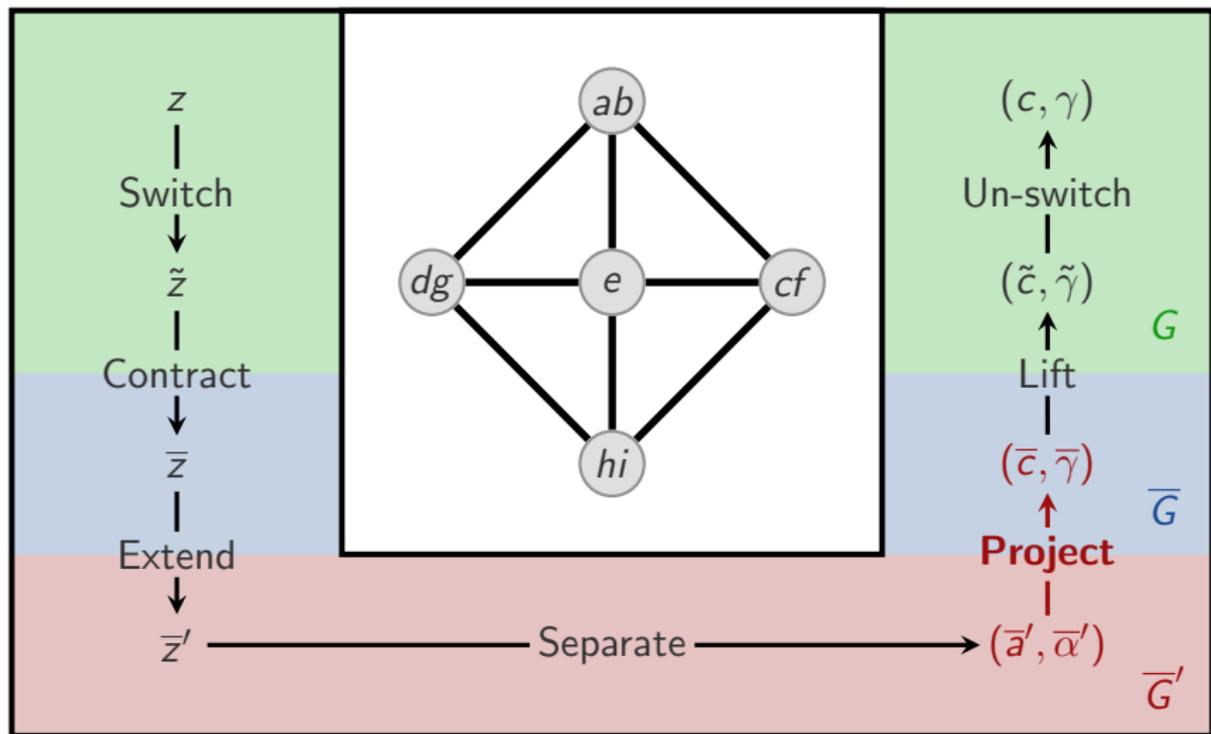
Outline of the Separation using Graph Contraction

Separate extended LP solution.



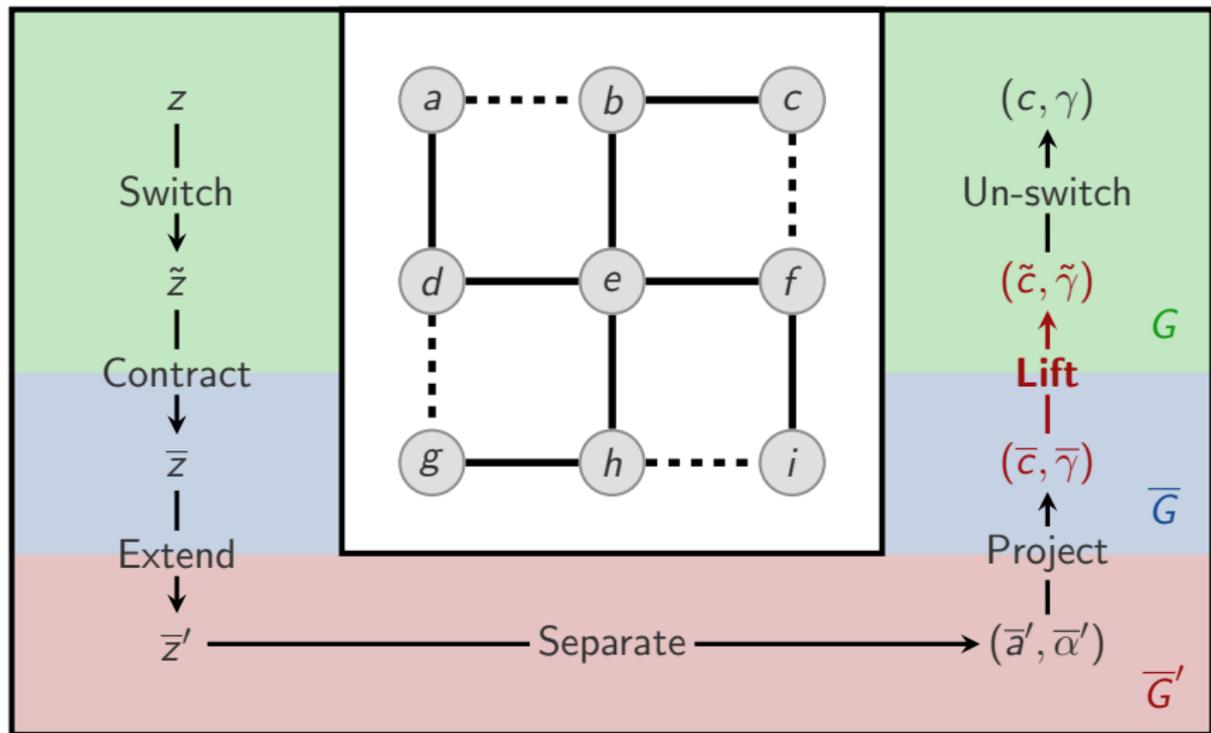
Outline of the Separation using Graph Contraction

Project out nonzero coefficients related to non-edges.



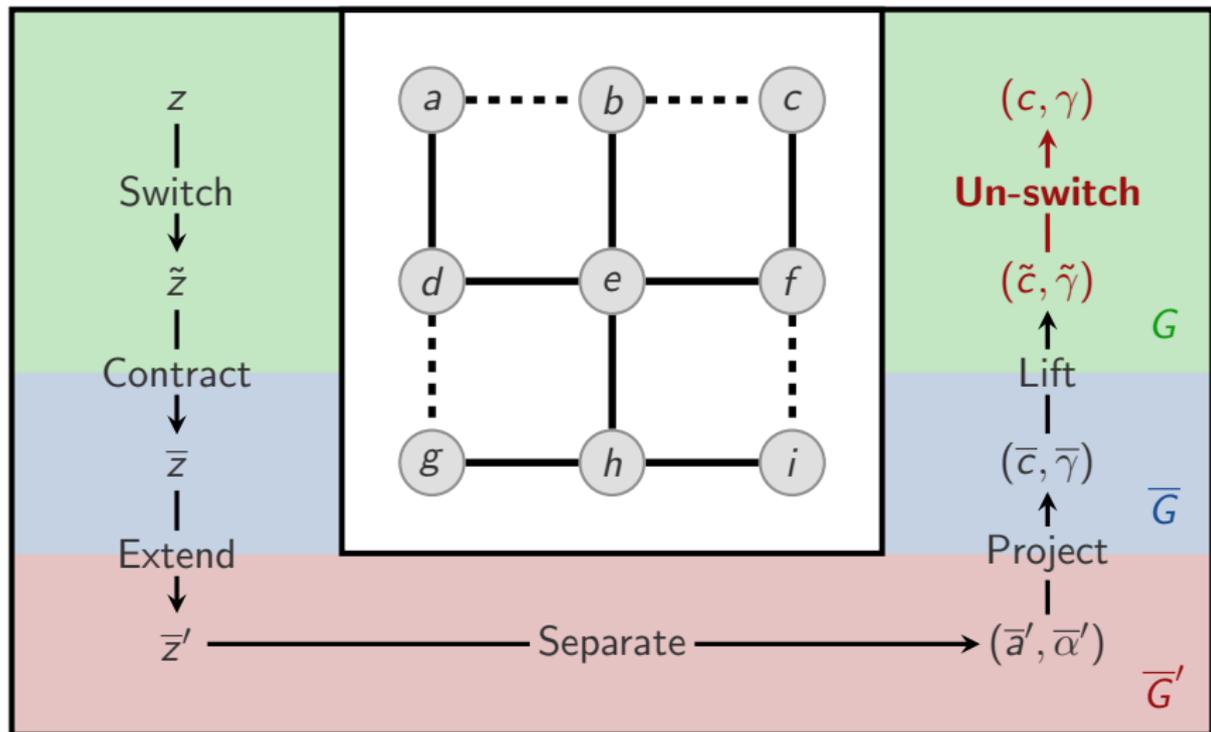
Outline of the Separation using Graph Contraction

Lift inequality.



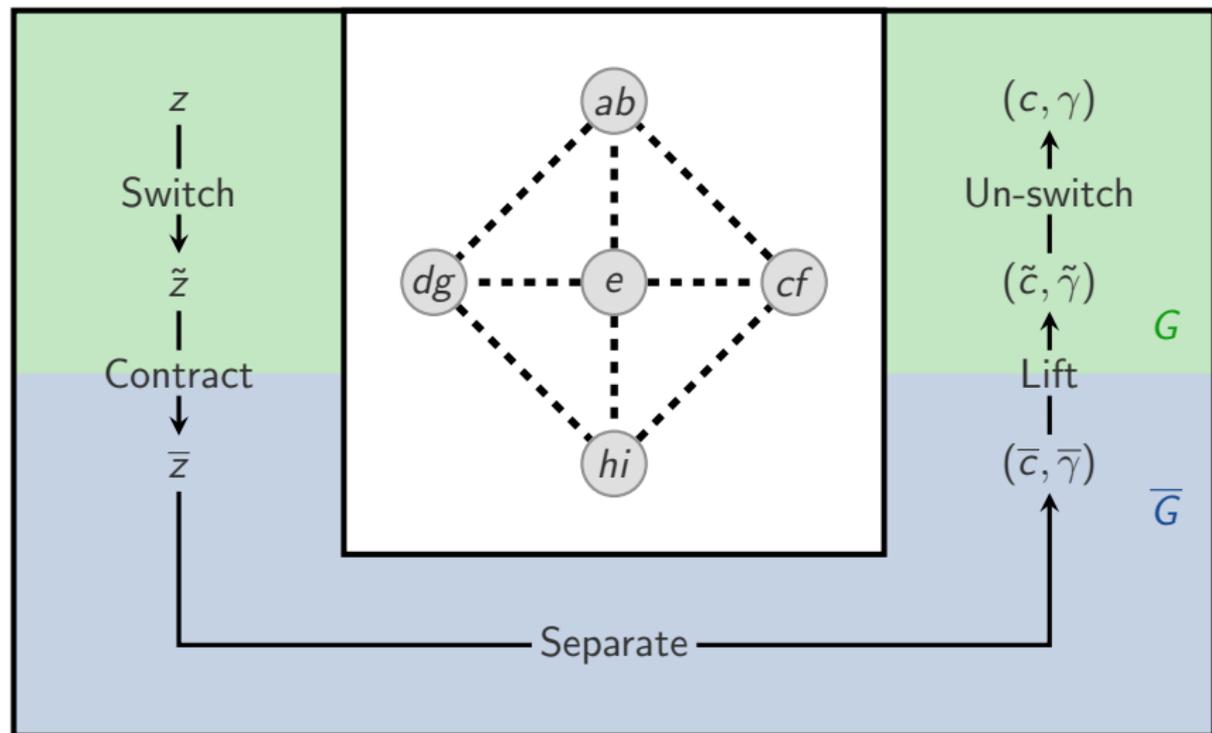
Outline of the Separation using Graph Contraction

Switch lifted inequality.



Outline of the Separation using Graph Contraction

In the scope of this talk, we omit the extension.



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Target cuts were introduced by [Buchheim, Liers, and Oswald](#).

Given:

- Polytope $P := \text{conv}\{x_1, \dots, x_n\} \subseteq \mathbb{R}^d$,
- Point $x^* \notin P$.

Target Cuts vs. Standard Separation

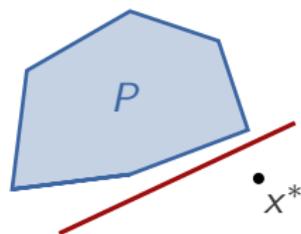
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Standard separation

Find a **valid** inequality $a^T x \leq \alpha$
that separates x^* from P .



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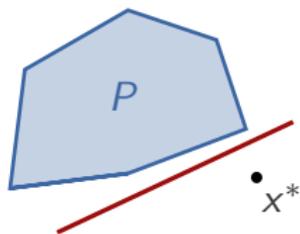
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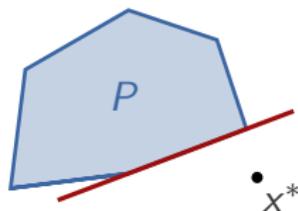
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Target cut separation

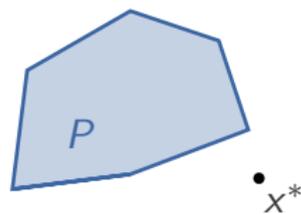
Find a **facet inducing** inequality $a^T x \leq \alpha$ that separates x^* from P .



Target Cuts in a Nutshell

Given:

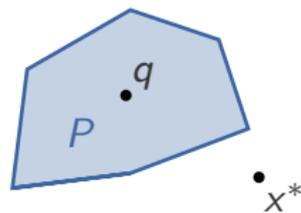
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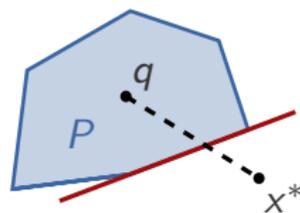
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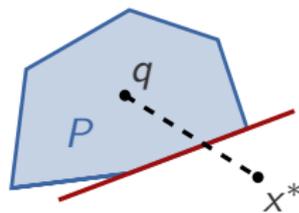
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Find the inequality $a^T x \leq \alpha$ which induces the facet of P that is intersected by the line $\overline{qx^*}$.

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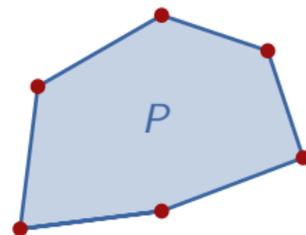
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Target Cut LP

$$\begin{aligned} \max \quad & a^T (x^* - q) \\ \text{s.t.} \quad & a^T (x_i - q) \leq 1, \text{ for } i = 1, \dots, n \\ & a \in \mathbb{R}^d. \end{aligned} \quad (\text{TC})$$

Main problem

(TC) has one row for each vertex of P .

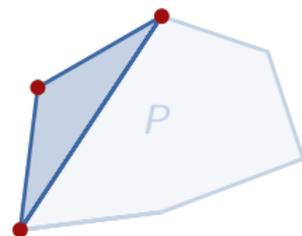


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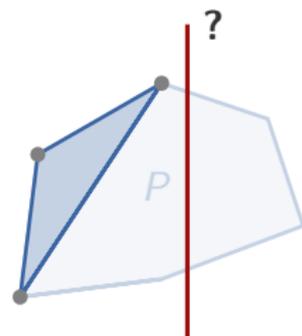
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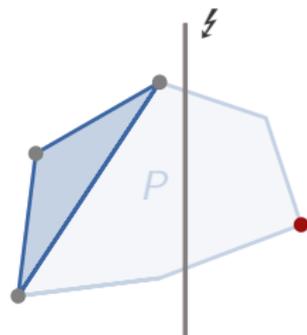
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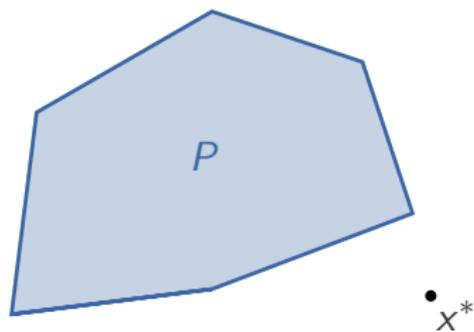
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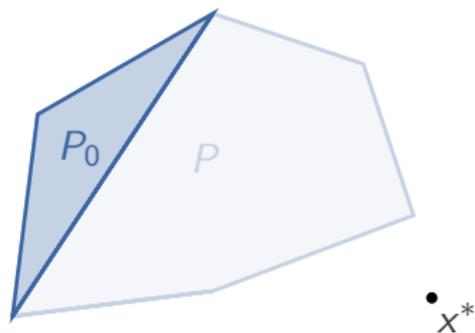
- 1 checks whether a given inequality $b^T x \leq \beta$ is valid for P ,
- 2 if not, provides at least one violating vertex of P .



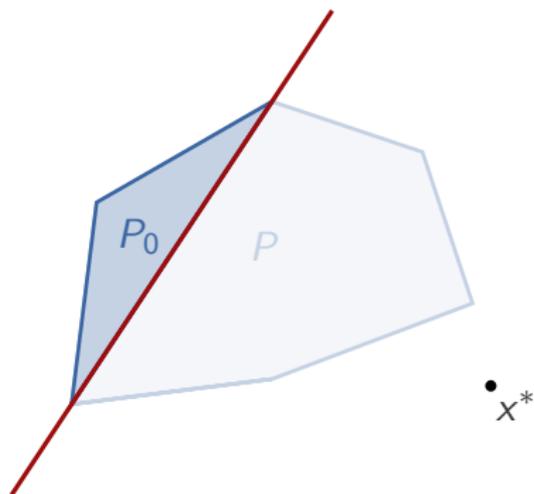
Delayed Row Generation: An Example



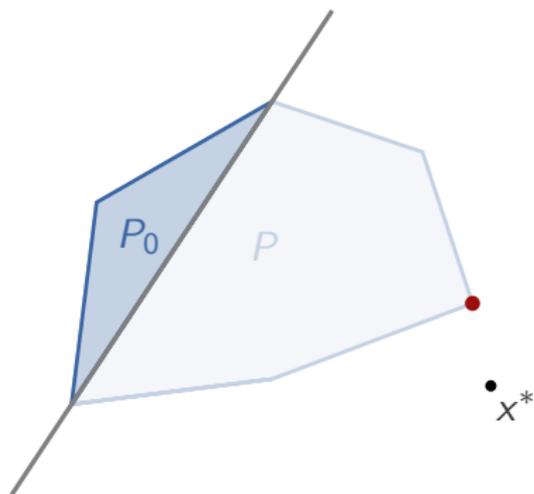
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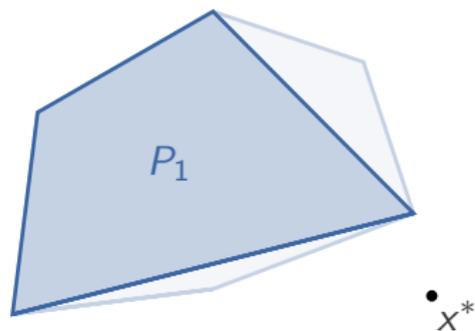
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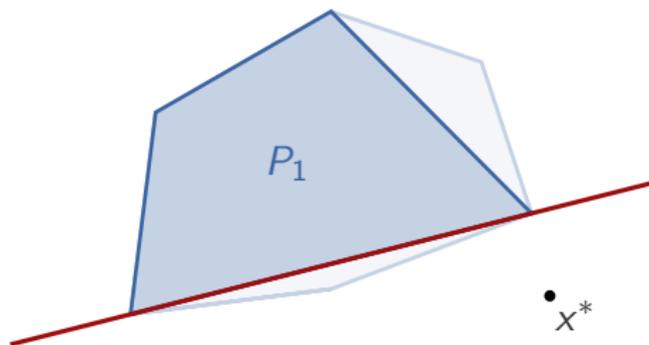
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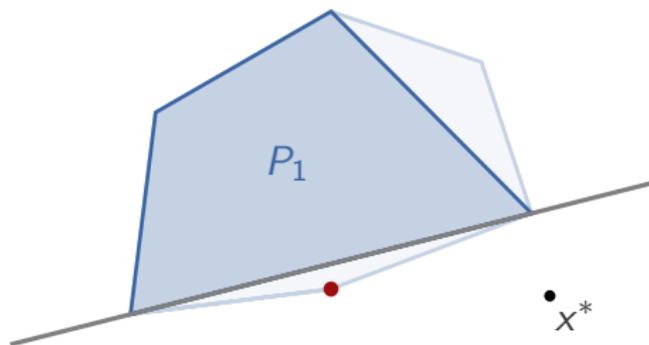
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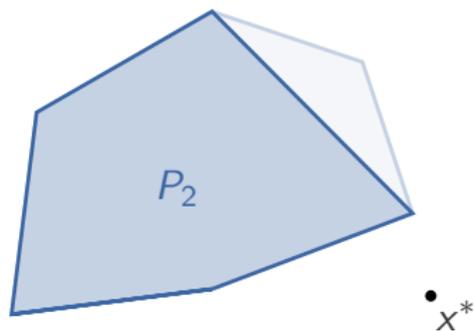
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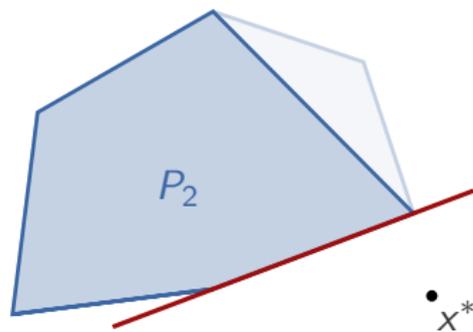
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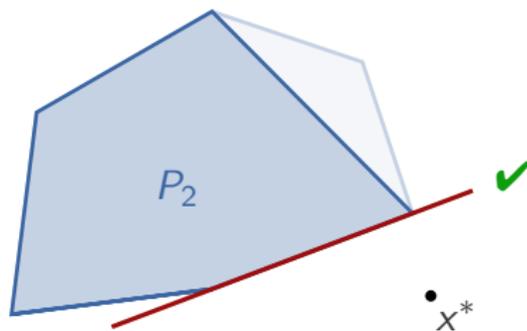
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Exact approach

- Solve $\max \{b^T x \mid x \in P\}$ for given b .
- Use of exact algorithm in each oracle call can slow down the overall target cut separation.

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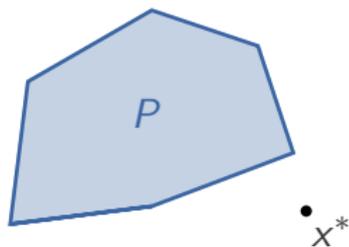
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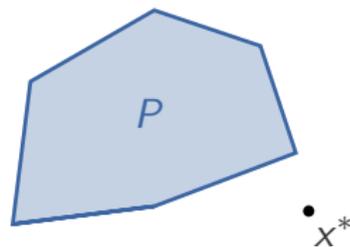
Oracle varieties

Try to find multiple violating vertices per oracle call.

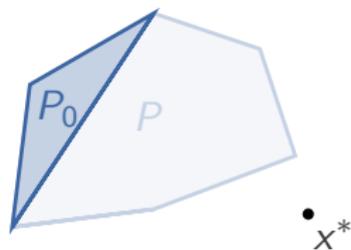
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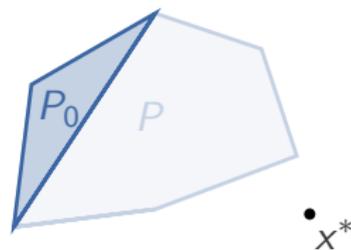
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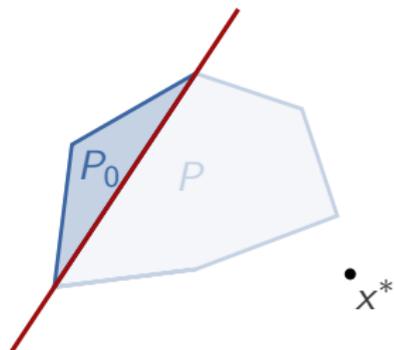
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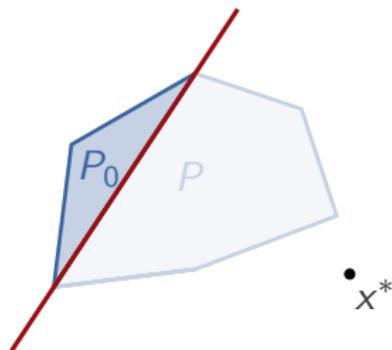
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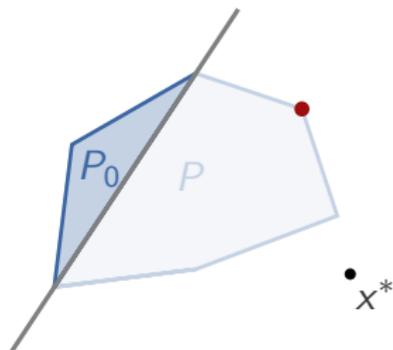
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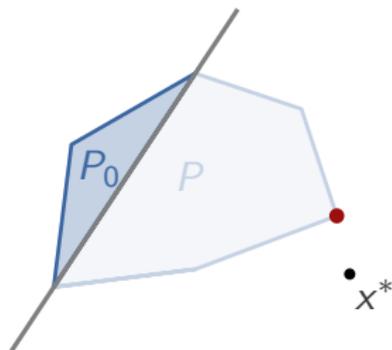
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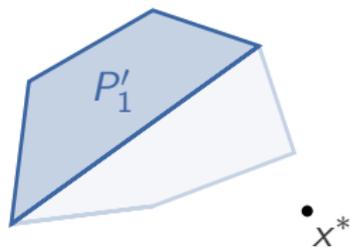
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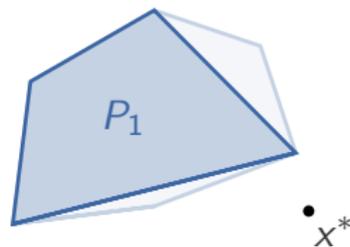
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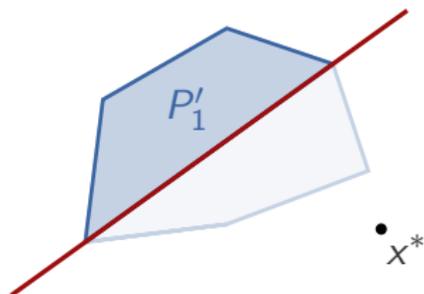
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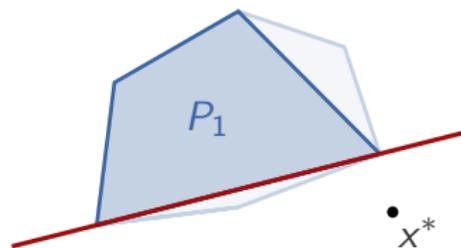
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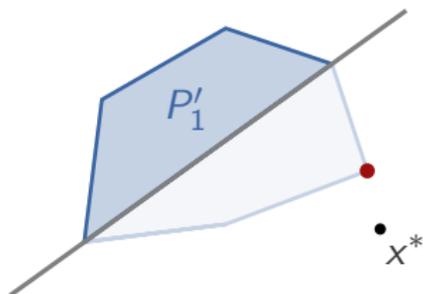
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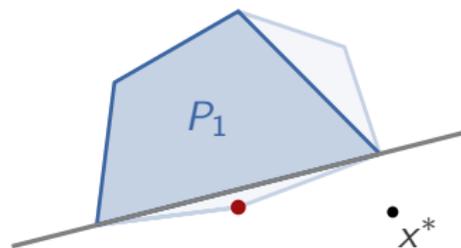
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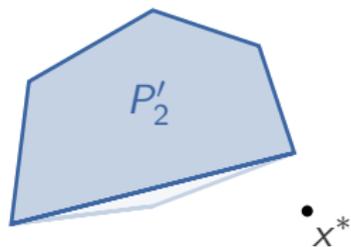
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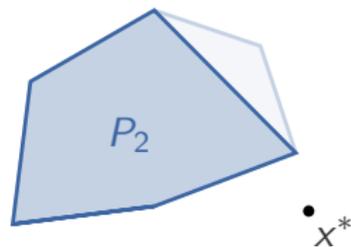
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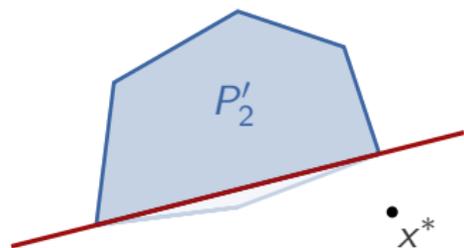
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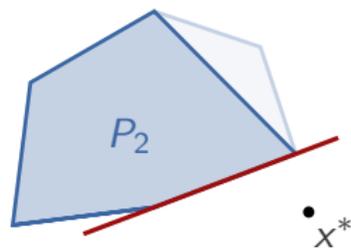
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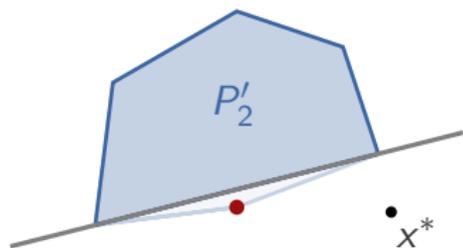
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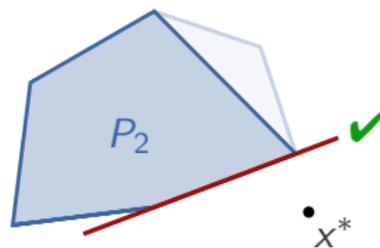
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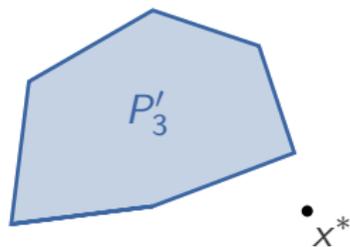
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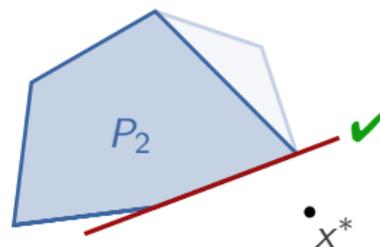
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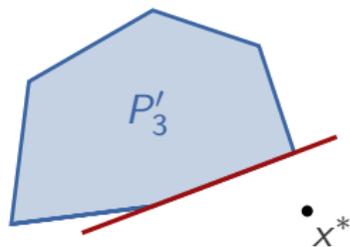
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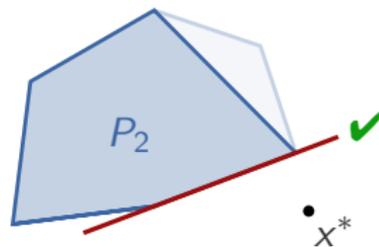
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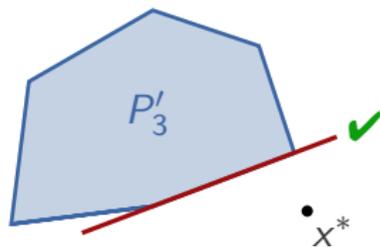
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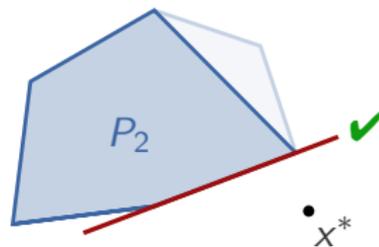
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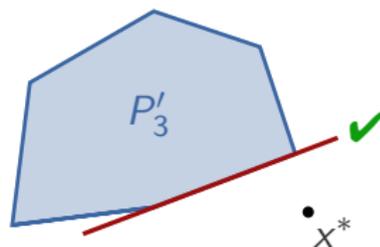
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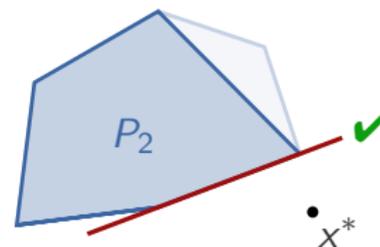
Heuristic approach



More but **faster** calls of the heuristic

vs.

Exact approach



Fewer but **slower** calls of the exact algorithm

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Graph contraction / selection

- Use graph contraction to reduce the size of the initial graph.
- If contracted graph is too large, select a connected subgraph:
 - at random,
 - prefer edges with an LP value close to 0.5,
 - ...

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Oracles for delayed row generation

- Exact algorithms:
 - **Branch & Cut**,
 - Branch & Bound using SDP relaxations.
- Heuristics:
 - **Kernighan-Lin** (multiple solution version),
 - Goemans-Williamson.

Test set

- Carried out a single B&C optimization of the problem `bqp250-1` with 250 nodes and 3339 edges [cf. [Biq Mac Library](#)].
- Extracted 42 intermediate LP solutions that were passed to the target cut separator.

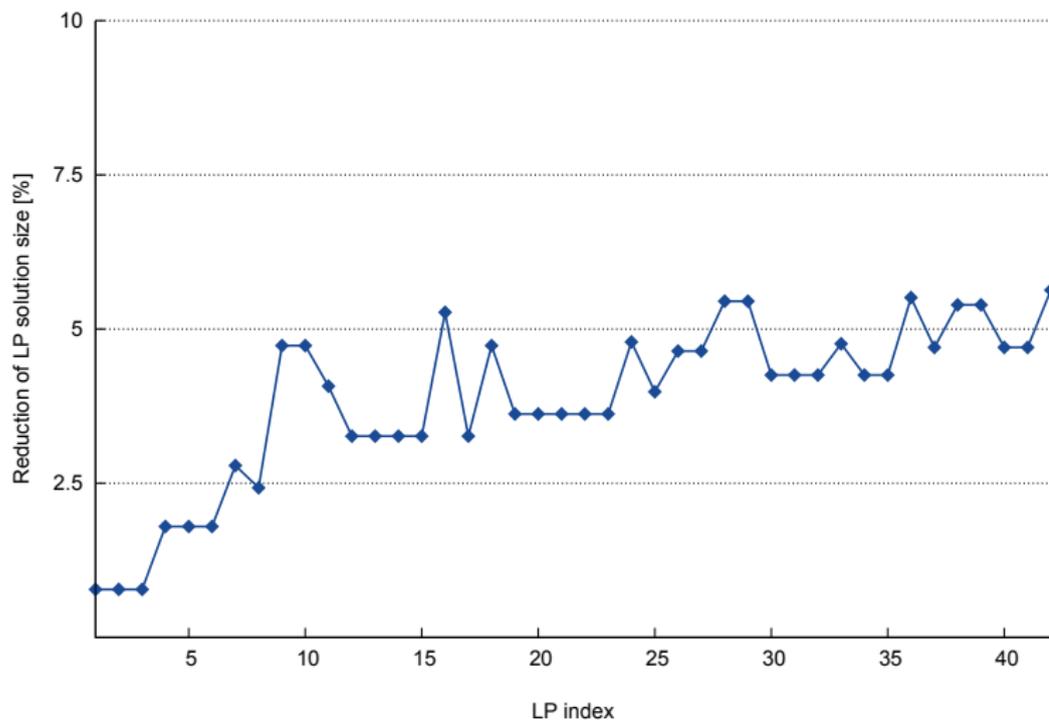
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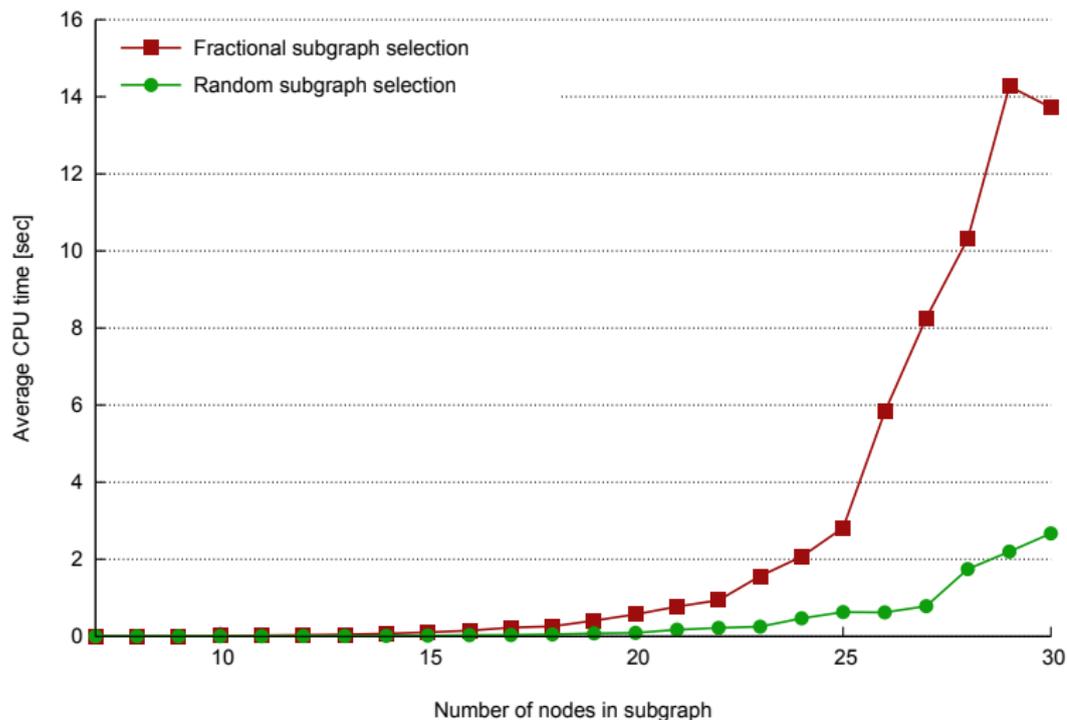
Measured quantities

- Average CPU time of the target cut separation over the 42 LP solutions.
- Rate of success, i. e., the percentage of the target cut separation attempts that found at least one cutting plane.

Reduction of LP Solution Size by Graph Contraction

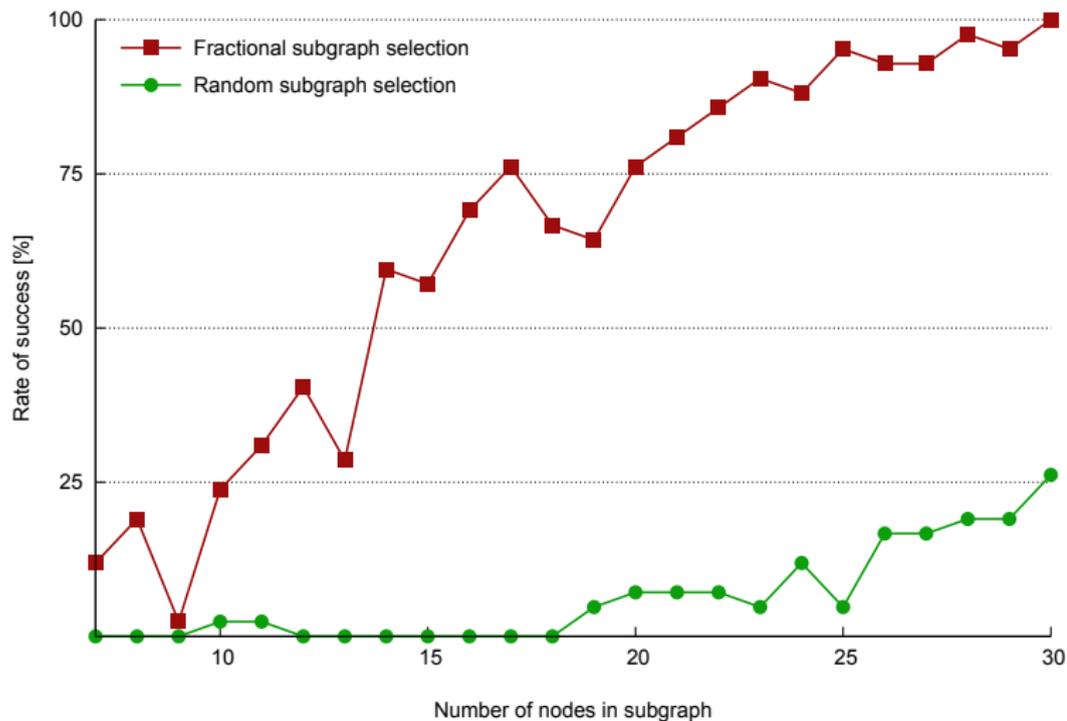


Average CPU Time with Delayed Row Generation

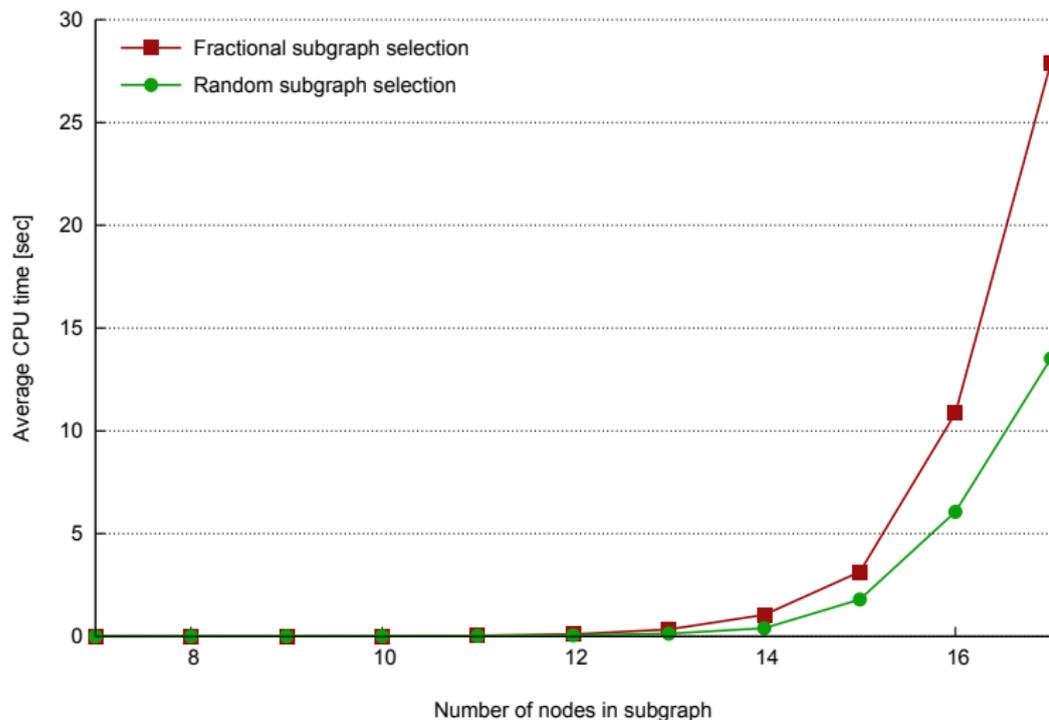


[Intel Xeon 2.8 GHz, 8GB shared RAM.]

Rate of Success with Delayed Row Generation

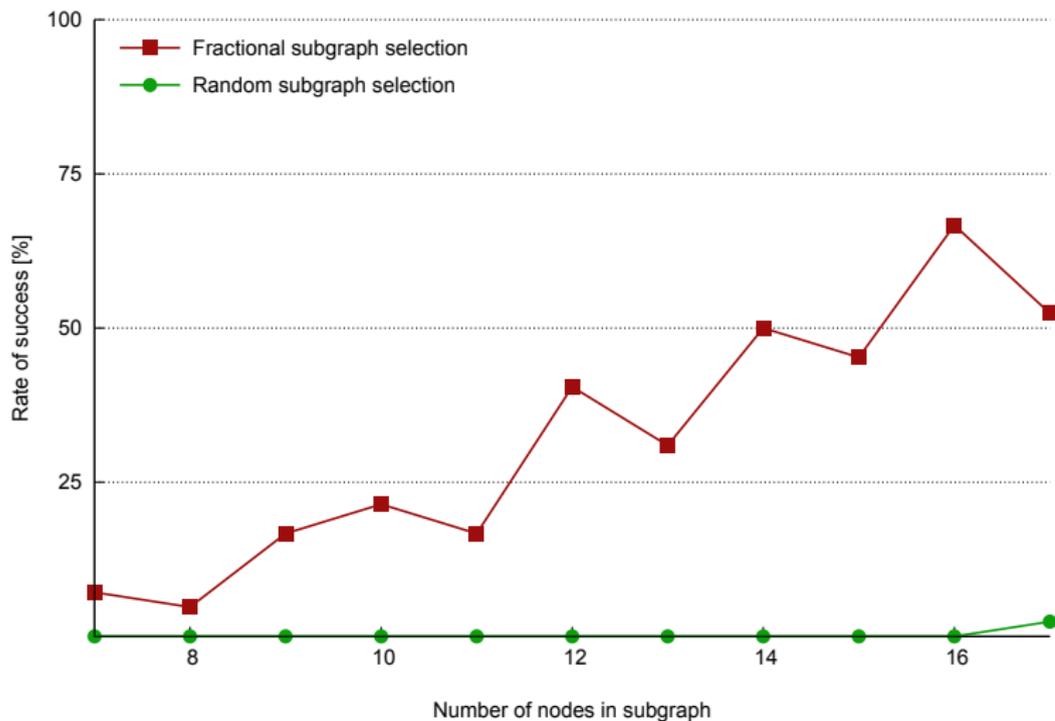


Average CPU Time without Delayed Row Generation



[Intel Xeon 2.8 GHz, 8GB shared RAM.]

Rate of Success without Delayed Row Generation



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Thank you for your attention!